AMUSED: A Multilingual Urdu/English Stance and Fake News Detection Corpus

Sehrash Safdar*, Muhammad Wasim*, Abdur Rehman†, Muhammad Usman Ghani‡
* Department of Computer Science, University of Management and Technology, Lahore (Sialkot Campus), Pakistan
Email: {sehrishsafdar,muhammad-wasim}@gmail.com, @skt.edu.pk
† Dept. of Computer Science, The University of Gujrat, Gujrat, Pakistan
Email: a.rehman@uog.edu.pk
‡ Dept. of Computer Science, University of Engineering and Technology, Lahore, Pakistan
Email: usman.ghani@kics.edu.pk

***Abstract*—Online fake news is a significant concern today, as many people rely on social media for news consumption. Although there are various datasets for detecting fake news, most are in English and primarily focus on news content. Only a few datasets include social context and user profile information. Furthermore, no multilingual (English/Urdu) event-based dataset exists specifically for fake news detection. This highlights the need for a comprehensive dataset with features such as user profiles, social interactions on posts, and news content on various events. To address this gap, this study collected a multilingual dataset (AMUSED) focused on recent events in Pakistan. This dataset contains information on 12 recent multi-domain events, 66 claims, 468 source posts, and 36,940 comments. The data set is labeled for stance detection and fake news detection. This data set includes all relevant social context, user profiling, and news content characteristics associated with the source posts. In addition, a benchmark study is presented to evaluate the performance of state-of-the-art models on the proposed dataset. BERT-Base-Multilingual-Cased model is trained for the stance detection task, achieving an 71% F1 score, whereas RoBERTa is used for fake news detection task achieving an F1 score of 79%.**

***Index Terms*—Pakistani Events, Multi-lingual dataset, Facebook, Instagram, Twitter**

I. Introduction

The last decade has witnessed exponential growth in the use of social media platforms such as Facebook, Instagram, and Twitter (X) with billions of active users. People rely on these social media platforms to get news as they provide a convenient and simple way to spread information [1]. Unfortunately, many people use these platforms to share misinformation to harm individuals, organizations, and government bodies [2]. For instance, fake news regarding the Punjab Group of Colleges in Lahore has recently been circulating on social media[1]. The rumor event that a 17-year-old girl was allegedly raped in the basement of the college building and later died after being transferred to Eve Care Hospital. This misinformation on social media has led to student protests and destroying college property. The news was spread using multiple languages content. In addition, it offered a rich social context that can be used to determine the veracity of the news. Therefore, it is critical to develop automated approaches to detect fake news in multiple languages and social contexts.

In recent years, many datasets related to fake news detection have been publicly released for the English language [3, 4]. These datasets have significantly advanced research for fake news detection as these datasets provide news content and social context information. For example, the RumorEval19 dataset comprised Twitter and Reddit discussions about rumors [4]. The source tweets are labeled as rumor or non-rumor, with related comments linked to the source post providing rich social context. In addition, the post comments in the dataset were also labeled to determine if the commenting user agreed or disagreed with the source post, a task referred to as stance detection. However, no public dataset is available for stance detection and fake news classification on multilingual datasets.

Although social media is used globally, users prefer to share their views in their language. For example, social media users in Pakistan prefer to use Urdu and Roman Urdu for posts and comments on social media [5]. Urdu is a low-resource language and lacks the resources necessary to train models for automated fake news detection. Only a very few datasets are available for fake news detection for the Urdu language [6, 7]. Unfortunately, these datasets have several shortcomings. First, these datasets only cover title text and do not provide user comments, likes, timestamps, and user profiling features . Second, the social media posts are usually in multiple languages. However, the datasets developed are only in the Urdu language. Third, these datasets lack additional social context information which can greatly aid in fake news classification.

This study have developed a multilingual Urdu/English stance and Fake News Detection Dataset (AMUSED) to tackle these challenges. It is derived from social media platforms Facebook, Instagram, and Twitter(X) and focuses on recent events in Pakistan. The dataset comprises 66 claims, 468 source posts, and 36,940 comments. Furthermore, we use state-of-the-art models to evaluate the performance for the stance detection and fake news classification task. In short, this study makes the following contributions:

- This study develop a Multilingual Urdu/English Stance and Fake News Detection Datasets (AMUSED) for de-

[1]https://www.dawn.com/news/1865600

tecting fake news, based on 12 recent events in Pakistan.
- This study provide guidelines for the manual annotation of comments by three human annotators for stance detection.
- This study analyze different models' performance for stance detection on the proposed dataset, with bert-base-multilingual-cased achieving the highest F1 score of 71%.
- In this study we train the RoBERTa model on our dataset to effectively detect fake news and achieve 79% F1 score.

The remaining paper is organized as follows: Section 2 reviews the literature focusing on previous datasets for fake news detection. Section 3 details the process of dataset collection. Section 4 describes the experimental setup and presents the results, while Section 5 offers conclusions from our study. The conclusion and limitations of our work are presented at the end.

II. Literature Review

This section reviews the research literature on the previously collected datasets for fake news detection and stance detection on social media. In the following subsections, we first discuss the content-based datasets, and then the social context-based datasets.

A. Content Based Datasets

In previous studies, we discussed the datasets that only contain news articles or headlines. Initially the Buzzfeed dataset contains fake and true news articles published on Facebook during the 2016 US election, totaling 182 observations [8]. The LIAR[2] dataset contained 12.6k hand-labeled brief statements from politifact.com on various news subjects [9]. It was a multilabel dataset with six labels. The ISOT[3] dataset is also a well-known textual dataset based on news articles used for various models to detect fake news [10, 11]. It contained 23,481 fake news articles and 21,417 real news articles, classified into two categories: Real and Fake. FEVER was a publicly available dataset that can be used for textual verification. The dataset included 185,445 claims derived from Wikipedia sentences that were verified without knowledge of the original sentence. Annotators classified claims as supported, refuted, or notenoughinfo [12]. Additionally, a dataset by the Kaggle data science community contains 7,796 news articles, categorized as true or false [13]. Over time news headlines or articles were not enough to detect fake news so researchers used social media platforms that were widely used for news, as people rely on social media posts for information [14]. Consequently, researchers have turned to social media platforms to detect fake news.

A dataset from twitter [4] relates to false information dissemination with distinct values for ID, title, author, and the main text of news articles microblog accounts to create a new environment for the posts [15]. The English dataset includes news stories from 2014 to 2018, sourced from the Huffington Post, National Public Radio, and Daily Mail, and was not publicly available. Another dataset contained COVID-19-related social media posts and news in English, while a separate dataset covers Twitter rumors and non-rumors during breaking news events [16]. Between July 2010 and November 2014, 260,227 YelpZip users left 608,598 reviews. These included 80,466 false reviews and 528,132 legitimate ones, considering that a single reviewer can submit multiple reviews [17]. The Rumoreval19 dataset contained discussions from Twitter and Reddit about rumors [4]. The dataset was labeled as true, false, or unverified and it included related ground truth. Additionally, there were datasets for Hindi false and true news, Chinese fake news, and Taiwan's Fair Trade Commission (FTC) discussion forum [17] for fake news detection. The Twitter dataset comprises tweet text related to widely spread fake news, with a total of 195,943 tweets initially collected [18].

B. Social Context Based Dataset

In the previous section, we discussed content-based datasets. These datasets contained information about news headlines, articles, and social media posts. However, in content-based datasets, no user interactions or social context features were involved. Social context refers to how users interact with news articles, such as publishing or sharing them on Twitter [19]. This section focuses on social context-based datasets that include user involvement and social media posts or news for detecting fake news. One such dataset was FakeNewsNet[5] containing information about news content and social context [20]. The dataset was sourced from two fact-checking platforms: Politifact and Gossipcop. Both platforms provide news articles labeled by professional fact-checkers and social context data. Meta attributes, such as text body, were included in the news.

Similarly, Fakeddit dataset[6] was developed with news content and social context information [4]. It contained one million samples of fake and real information divided into six categories. It included binary ground truths for classifying real and fake news, as well as three and six-class classifications for more detailed analysis. It also contained comments from the Reddit platform about each post. Another dataset was developed by [21] that contained social interactions from the Reddit platform. The Reddit-based fake news detection dataset called Reddit-comments comprised 12,597 threads and over 662,000 comments. The Twitter15 and Twitter16 datasets[7] focused on detecting rumors on Twitter by using social context features, offering labeled samples for training, development, and testing [22].

After a thorough review of content-based, and context-based datasets, the datasets focused on fake news primarily concentrate on the features of news content, with only a few incorporating social context and text features. Limited

[2]https://www.kaggle.com/datasets/csmalarkodi/liar-fake-news-dataset

[3]https://www.kaggle.com/datasets/emineyetm/fake-news-detection-datasets

[4]The dataset can be downloaded from: https://www.kaggle.com

[5]https://github.com/KaiDMML/FakeNewsNet

[6]https://opendatalab.com/OpenDataLab/Fakeddit/explore/main

[7]https://github.com/OwenLeng/rumor-detection-include-twitter15-twitter16data-

TABLE I
COMPARISON OF OUR DATASET (AMUSED) WITH OTHER PUBLICLY AVAILABLE DATASETS IN THIS DOMAIN

Dataset	News Content Features		Social Context Features		
	Headlines\Articles	Social Media Posts	Social Interactions	User Profiling	Timestamp
Buzzfeed	✓	×	×	×	×
LIAR	✓	×	×	×	✓
ISOT	✓	×	×	×	×
Feverr	✓	×	×	×	×
Twitter	✓	✓	×	×	×
Fakeddit	×	✓	✓	×	✓
FakeNewsNet	✓	×	✓	×	✓
Rumoreval19	×	✓	✓	×	×
FNC-1	✓	✓	×	×	×
Reddit-comments	×	×	✓	×	×
AMUSED	✓	✓	✓	✓	✓

attention was paid to multi-lingual, user profiling, and social context features as shown in Table I.

Although several datasets about fake news detection were available, none provided information on news content, user comments, and user profiles simultaneously. Additionally, the lack of comprehensive datasets with rich modalities makes it challenging to fairly compare the results of previous studies that utilize various modalities for detection. Most existing research relies on news content features and does not consider social context and user profile features, unintentionally overlooking crucial information.

TABLE II
COMPARISON WITH PREVIOUS DATASETS FOR THE STANCE DETECTION TASK

Dataset	Total comments	agree%	disagree%	query%	comment%
twitter dataset [1]	3,000	29.5	17.7	15.1	37.7
RumorEval2019 [23]	8,574	13.8	7	7	72
RumorEval2017 [24]	3,685	18	7.4	8.3	66.1
FNC1 [25]	2,587	7.4	2	17.7	72.8
AMUSED	36,940	34.1	8.6	7.6	49.5

In our analysis, most of these datasets were in English and consisted only of news content. Only a few include comments and social context. Currently, no dataset combines social context, user profiling features, and news content, associated with the source posts. There are very few datasets that focus on stance detection concerning fake news as shown in Table II. This highlights the need for a comprehensive dataset. To address this gap, we collected a dataset focused on current events in Pakistan, encompassing multiple languages and domains. This ultimately allows us to efficiently and accurately identify fake and real news for English, Urdu, and Roman Urdu.

III. DATASET DEVELOPMENT

In this study a multilingual Urdu/English stance and fake news detection (AMUSED) dataset was collected because little attention was paid to multilingual fake news detection datasets. Data was collected on recent events in Pakistan in different languages. Specifically, data was collected about 12 Pakistani events from Facebook, Instagram, and Twitter (formally, X). Different hashtags and related keywords are used to manually collect data from social media platforms based on events identified by fact-checking websites and multiple news websites such as Dawn and Geo News. Posts about recent events in Pakistan from September 15, 2024, to October 15, 2024, are specifically gathered. Only social media posts relevant to the claims are collected. 66 claims about 12 recent events, 468 original posts, and 36,940 comments were collected from various popular social media platforms such as Facebook, Instagram, and Twitter. The dataset is stored in CSV format and contains all the information available on github[8]. The collection of the dataset involves a three-phase process as illustrated in Figure 1.

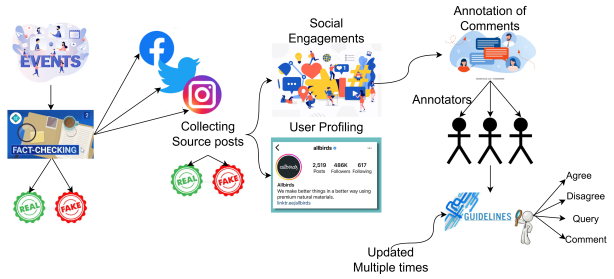

Fig. 1. The process of dataset collection and annotation

A. Collecting Source Posts

In the first phase, we collect claims from various fact-checking and news websites related to different events in Pakistan, encompassing social, cultural, and political aspects. Following this, we gather source posts from Facebook, Instagram, and Twitter, which are labeled as true or false according to the claims.

B. Social Engagements

In the second phase, we collected data on various social interactions related to source posts. The social engagement

[8]https://github.com/sehrishsafdar/AMUSED-Dataset.git

features we gathered include the number of likes, comments, views, shares, timestamps, comment text, and the names of commenters. Additionally, we recorded user profile features such as the number of followers, total posts, the URL of the profile picture, and the user's location.

1) Annoation Process: The data were annotated by three qualified annotators. To assess the quality of our annotations, we randomly selected 10% of the comments and asked the annotators to label them manually. For example, sample comments and respective guidelines for a source post *Twitter (X) has been unbanned in Pakistan* are presented below:

- **Agree**: The author of the comment supports the source post with positive words or reactions.
  Example(yes it's Working without VPN)
- **Disagree**: The author of the comment denies the source post or the event of the source post.
  Example (still ban bro it's been almost 6 months I'm facing the issue)
- **Query**: Any statement that contains a question mark or asks a question.
  Example(reallyyyyyyy?)
- **Comment**: The author of the comment posted a statement without clearly defining its meaning.
  Example(I have online work)

An iterative approach to develop the guidelines was used. The main advantage of having these guidelines is to ensure consistent annotation. The annotation process is crucial for ensuring the accuracy and consistency of any dataset. The comments are labeled for the stance detection task, which helps us accurately differentiate between fake and real news. It helps us identify the nuances of public opinion and sentiment related to various posts. By carefully analyzing this interaction data, we aim to gain deeper insights into how misinformation spreads and how different users perceive it.

Cohen's Kappa for inter-annotator agreement, which was found to be 0.81, indicates an almost perfect agreement between the annotators.

C. User Features

In the third phase, user features related to source posts, such as username, number of followers, number of following, number of posts, user biography, and whether the user is verified are collected.

66 claims are gathered, comprising 47 true claims and 19 false claims from fact-checking and news websites. After compiling these claims, various posts from social media platforms Facebook, Instagram, and Twitter. Specifically, 77 true posts and 45 false posts, along with 6,975 comments on Twitter are gathered. From Instagram, 129 true posts, 48 false posts, and 6,736 comments are collected. For Facebook, 87 true posts, 82 false posts, and a total of 23,137 comments are obtained.

In Table III, the authors present a detailed annotation of comments, all of which have been manually annotated according to the updated guidelines. For the task of stance detection, they categorize comments into four groups: agree, disagree, query, and comment. The sample of the dataset is presented in Figure 2.

TABLE III
AMUSED DATASET: THE DISTRIBUTION OF POST COMMENTS ACROSS DIFFERENT SOCIAL MEDIA PLATFORMS

Platform	Comments	Query	Agree	Disagree
Facebook	11,663	1,309	7,653	1,780
Instagram	2,923	798	2,545	918
Twitter	3,704	717	2,421	513
Total	18,290	2,824	12,619	3,211

IV. Experimental setup and Results

In this section, this study first outlines the experimental setup of various models on the curated dataset. In the following section, they present the results of these models on the dataset in comparison to previous state-of-the-art techniques.

A. Experimental setup

This study conducted experiments using Google Colab[9] with GPU support, combined with Python libraries such as Transformers[10], Keras, and PyTorch[11]. Our evaluation of the models' performance includes metrics such as Precision (P), Recall (R), F1-measure (F1), and Accuracy (A).

B. Baseline Models

This section discussed the baseline models of stance detection and fake news detection. For stance detection, this study compare their proposed methodology with the following two baselines:

- **Branch LSTM** [26] utilized an LSTM neural network architecture for stance detection on the SemEval-2017 dataset, which involves Twitter statements categorized as agree, disagree, query, or comment.
- **Hybrid model CNN+LSTM** [25] utilized CNN+LSTM model with principal component analysis (PCA) technique for dimension reduction and chi-square technique for feature selection. They used the FNC1 dataset to predict stance as agree, disagree, query, or comment

For fake news detection, this study performed a comparison with the following baselines:

- **Ensemble Learning** [10] used machine learning models Decision tree, Randon forest, and Extra tree classifier for fake news detection on two benchmark datasets LIAR and ISOT by using only title of news.
- **Machine Learning Classifiers** [8] used Random forest, Naive Bayes, and Passive aggressive classifier for fake news detection on the Buzzfeed dataset by using news titles with and without preprocessing.
- **Modified Bi-LSTM method** [1] used LSTM model with modified layers for fake news detection on Twitter by using tweet text, retweets, and likes.

[9]https://colab.research.google.com/
[10]https://huggingface.co/docs/transformers/main/en/index
[11]https://pytorch.org/

	id	sr	postid	title	label_x	posturl	image	likescount	timestamp	commentscount	views	shares	username	followers	bio	user/profileUrl	isverified	username	comment	label_y
2	C1		1	وفاق اردو پوز 1	FALSE	https://we	1	25000	11\8\2024	1704		567	FUUASTIAI	18000	the purpo	https://web.facet	FALSE	Mushtaq	انعام انعام ہی ہوتا ہے	agree
3	C1		1	وفاق اردو پوز 1	FALSE	https://we	1	25000	11\8\2024	1704		567	FUUASTIAI	18000	the purpo	https://web.facet	FALSE	Muhamm	کھجور کی گٹھلی دے د	disagree
4	C1		1	وفاق اردو پوز 1	FALSE	https://we	1	25000	11\8\2024	1704		567	FUUASTIAI	18000	the purpo	https://web.facet	FALSE	Ch Zabeh	انعام انعام ہی ہوتا ہے	agree
5	C1		1	وفاق اردو پوز 1	FALSE	https://we	1	25000	11\8\2024	1704		567	FUUASTIAI	18000	the purpo	https://web.facet	FALSE	Muhamm	tujhey gutli hi m	comment
6	C1		1	وفاق اردو پوز 1	FALSE	https://we	1	25000	11\8\2024	1704		567	FUUASTIAI	18000	the purpo	https://web.facet	FALSE	Muhamm	Cash de detey	comment
7	C1		1	وفاق اردو پوز 1	FALSE	https://we	1	25000	11\8\2024	1704		567	FUUASTIAI	18000	the purpo	https://web.facet	FALSE	شان مصطفیٰ	bhai date to che	comment
8	C1		1	وفاق اردو پوز 1	FALSE	https://we	1	25000	11\8\2024	1704		567	FUUASTIAI	18000	the purpo	https://web.facet	FALSE	Prince Ish	zabardast	agree
9	C1		1	وفاق اردو پوز 1	FALSE	https://we	1	25000	11\8\2024	1704		567	FUUASTIAI	18000	the purpo	https://web.facet	FALSE	Shah Zami	phir khujoor ko j	comment

Fig. 2. Sample of Created Dataset

- **Enhanced LSTM+BERT** [27] used the BERT model with LSTM layers for the fake news classification based on news titles for Politifact and Gossipcop datasets.

C. Results and Discussion

This section presented a thorough comparison of the curated dataset with stance detection baselines and fake news detection baselines on various methods. Table IV illustrated the results of the *AMUSED* dataset on two baseline models and they also trained their dataset on multilingual BERT base cased model for the stance detection task achieving 72% F1 which is higher than both baselines. In the Table IV and Table V, A represents accuracy, F1 represents F1-score, P denotes precision, and R stands for recall.

TABLE IV
PERFORMANCE COMPARISON FOR STANCE DETECTION ON OUR AMUSED DATASET

Algorithm	P	R	A	F1
Branch LSTM[26]	0.71	0.63	0.61	0.62
CNN+LSTM[25]	0.49	0.46	0.51	0.52
Multilingiual BERT	0.67	0.52	0.71	0.72

Table V illustrated the results of the fake news detection model on multiple baselines. The transformer-based model RoBERTa outperformed all baseline models and achieved a 79% F1 score on our curated *AMUSED* dataset. They used transformer-based models for both tasks because transformer-based models handle complex patterns through contextualized embeddings. They are more effective for datasets with multiple features and are specifically designed to capture subtle nuances. Additionally, they leverage extensive pre-trained knowledge, making them particularly suitable for tasks such as fake news detection.

TABLE V
PERFORMANCE COMPARISON FOR FAKE NEWS DETECTION ON OUR AMUSED DATASET

Algorithm	P	R	A	F1
Ensemble learning[10]	0.53	0.56	0.62	0.63
Naïve Bayes[8]	0.57	0.51	0.56	0.57
Passive Aggressive[8]	0.61	0.65	0.61	0.6
Random Forest[8]	0.73	0.69	0.63	0.62
Modified Bi-LSTM[1]	0.71	0.65	0.68	0.67
LSTM+BERT[27]	0.69	0.68	0.66	0.65
RoBERTa	0.72	0.69	0.78	0.79

V. CONCLUSION

In this paper, the study collected a diverse dataset using online social media platforms such as Facebook, Instagram, and Twitter. Their dataset included social engagements, user profile features, news content features, and spatiotemporal features. they collect recent events from Pakistan and gathered claims from fact-checking and news websites. After collecting these claims, they collected relevant source posts and gathered all their features. Additionally, they collected user profile information. Once we had all the necessary data, we hired a team of three annotators who manually annotated comments as agree, disagree, query, or comment based on the guidelines we developed. The authors also conducted experiments on their AMUSED dataset and achieved a 71% F1 score for the stance detection task by using a multilingual BERT base cased model and a 79% F1 score for the fake news detection task by using the RoBERTa model. The transformer-based models outperformed all the baselines because they effectively handle the complex features of the dataset. This study has certain limitations, as they gathered data from only three online social media platforms. In the future, the authors plan to expand their dataset by incorporating additional social media platforms as well as multimodal information. Additionally, their aim is to enhance the ability to detect fake news by employing both stance and fake news detection methods, which will allow for more efficient identification of false information.

DATA AVAILABILITY

The Dataset is publically available on github https://github.com/sehrishsafdar/AMUSED-Dataset.git

ACKNOWLEDGMENT

This research work was funded by the Higher Education Commission (HEC), Pakistan, through the National Research Program for Universities (NRPU) grant under the project Ref No. 20-16597/NRPU/R&D/HEC/2021 2021.

REFERENCES

[1] C. Agrawal, A. Pandey, and S. Goyal, "Fake news detection system based on modified bi-directional long short term memory," *Multimedia Tools and Applications*, vol. 81, no. 17, pp. 24199–24223, 2022.

[2] L.-C. Cheng, Y. T. Wu, C.-T. Chao, and J.-H. Wang, "Detecting fake reviewers from the social context with a graph neural network method," *Decision Support Systems*, vol. 179, p. 114150, 2024.

[3] A. Zubiaga, G. Wong Sak Hoi, M. Liakata, and R. Procter, "Pheme dataset of rumours and non-rumours," 2016.

[4] A. M. Luvembe, W. Li, S. Li, F. Liu, and G. Xu, "Dual emotion based fake news detection: A deep attention-weight update approach," *Information Processing & Management*, vol. 60, no. 4, p. 103354, 2023.

[5] A. Atif, A. Zafar, M. Wasim, T. Waheed, A. Ali, H. Ali, and Z. Shah, "Cyberbullying detection and abuser profile identification on social media for roman urdu," *IEEE Access*, 2024.

[6] R. Salahuddin and M. Wasim, "Automatic identification of urdu fake news using logistic regression model," in *2022 16th international conference on open source systems and technologies (ICOSST)*, pp. 1–6, IEEE, 2022.

[7] Z. Iqbal, F. M. Khan, and I. U. Khan, "Fake news identification in urdu tweets using machine learning models," *The Asian Bulletin of Big Data Management*, vol. 4, no. 1, pp. Science–4, 2024.

[8] A. Sharma, M. Sharma, and R. K. Dwivedi, "Exploratory data analysis and deception detection in news articles on social media using machine learning classifiers," *Ain Shams Engineering Journal*, vol. 14, no. 10, p. 102166, 2023.

[9] W. Y. Wang, "" liar, liar pants on fire": A new benchmark dataset for fake news detection," *arXiv preprint arXiv:1705.00648*, 2017.

[10] S. Hakak, M. Alazab, S. Khan, T. R. Gadekallu, P. K. R. Maddikunta, and W. Z. Khan, "An ensemble machine learning approach through effective feature extraction to classify fake news," *Future Generation Computer Systems*, vol. 117, pp. 47–58, 2021.

[11] S. Safdar and M. Wasim, "Rafah: Roberta fine-tuned model and a hybrid features set for fake news detection," in *2024 18th International Conference on Open Source Systems and Technologies (ICOSST)*, pp. 1–6, IEEE, 2024.

[12] J. Thorne, A. Vlachos, C. Christodoulopoulos, and A. Mittal, "Fever: a large-scale dataset for fact extraction and verification," *arXiv preprint arXiv:1803.05355*, 2018.

[13] B. Koloski, T. S. Perdih, M. Robnik-Šikonja, S. Pollak, and B. Škrlj, "Knowledge graph informed fake news classification via heterogeneous representation ensembles," *Neurocomputing*, vol. 496, pp. 208–226, 2022.

[14] S. Safdar and M. Wasim, "Dfn-scnc: Detecting fake news based on social context and news content: A hybrid approach using bert and bi-gru," in *2024 International Conference on Frontiers of Information Technology (FIT)*, pp. 1–6, IEEE, 2024.

[15] D. G. Dev, V. Bhatnagar, B. S. Bhati, M. Gupta, and A. Nanthaamornphong, "Lstmcnn: A hybrid machine learning model to unmask fake news," *Heliyon*, vol. 10, no. 3, 2024.

[16] J. Alghamdi, Y. Lin, and S. Luo, "Towards covid-19 fake news detection using transformer-based models," *Knowledge-Based Systems*, vol. 274, p. 110642, 2023.

[17] D. Zhang, W. Li, B. Niu, and C. Wu, "A deep learning approach for detecting fake reviewers: Exploiting reviewing behavior and textual information," *Decision Support Systems*, vol. 166, p. 113911, 2023.

[18] L. Peng, S. Jian, Z. Kan, L. Qiao, and D. Li, "Not all fake news is semantically similar: Contextual semantic representation learning for multimodal fake news detection," *Information Processing & Management*, vol. 61, no. 1, p. 103564, 2024.

[19] K. Shu, X. Zhou, S. Wang, R. Zafarani, and H. Liu, "The role of user profiles for fake news detection," in *Proceedings of the 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, (Vancouver, British Columbia, Canada), pp. 436–439, ACM, Aug. 2019.

[20] K. Shu, D. Mahudeswaran, S. Wang, D. Lee, and H. Liu, "Fakenewsnet: A data repository with news content, social context, and spatiotemporal information for studying fake news on social media," *Big data*, vol. 8, no. 3, pp. 171–188, 2020.

[21] V. Setty and E. Rekve, "Truth be told: Fake news detection using user reactions on reddit," in *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, pp. 3325–3328, 2020.

[22] A. A. B. Cavalcante, P. M. S. Freire, R. R. Goldschmidt, and C. M. Justel, "Early detection of fake news on virtual social networks: A time-aware approach based on crowd signals," *Expert Systems with Applications*, vol. 247, p. 123350, 2024.

[23] G. Gorrell, K. Bontcheva, L. Derczynski, E. Kochkina, M. Liakata, and A. Zubiaga, "Rumoureval 2019: Determining rumour veracity and support for rumours," *arXiv preprint arXiv:1809.06683*, 2018.

[24] L. Derczynski, K. Bontcheva, M. Liakata, R. Procter, G. W. S. Hoi, and A. Zubiaga, "Semeval-2017 task 8: Rumoureval: Determining rumour veracity and support for rumours," *arXiv preprint arXiv:1704.05972*, 2017.

[25] M. Umer, Z. Imtiaz, S. Ullah, A. Mehmood, G. S. Choi, and B.-W. On, "Fake news stance detection using deep learning architecture (cnn-lstm)," *IEEE Access*, vol. 8, pp. 156695–156706, 2020.

[26] E. Kochkina, M. Liakata, and I. Augenstein, "Turing at semeval-2017 task 8: Sequential approach to rumour stance classification with branch-lstm," *arXiv preprint arXiv:1704.07221*, 2017.

[27] N. Rai, D. Kumar, N. Kaushik, C. Raj, and A. Ali, "Fake news classification using transformer based enhanced lstm and bert," *International Journal of Cognitive Computing in Engineering*, vol. 3, pp. 98–105, 2022.